

Recovering Unimodal Latent Patterns of Change by Unfolding Analysis: Application to Smoking Cessation

data
→ Analysis
methods

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A new model of change is proposed, based on the assumption that cognitive and behavioral processes of change basically follow inverse-U-shaped patterns of variation as smokers move toward effective change; Each process is first increasingly used, up to a maximum value, and then decreases. It is argued that such a model of data is properly dealt with by unfolding models specially designed for those cases. A theoretical foundation for an unfolding model of change is proposed, based on probabilistic reasoning first developed by D. Andrich and G. Luo (1993). An illustrative analysis on responses of 140 French smokers to C. C. DiClemente and J. O. Prochaska's (1985) Processes of Change Questionnaire is presented, which yields a very satisfactory unidimensional solution, along which items' locations are in convergence with previous longitudinal studies in the stage-of-change tradition and smokers' locations appear to be a good predictor of actual quitting.

Numerous latent trait models for the measurement of attitudes and cognitive abilities have been proposed (Andrich, 1978b; Bock, 1972; Lord, 1952; Masters, 1982; Muraki, 1992; Samejima, 1969) that have expanded and sophisticated probabilistic response models initially proposed by Rasch (1960) in a tradition of psychological measurement that could be traced to Thurstone's (1927, 1928) seminal works. Extensions in the use of these models from structural traits measurement to longitudinal data analysis have been proposed (Fischer, 1989; Fischer & Parzer, 1991). In the structural equation modeling tradition, latent growth models are also available for the analysis of change (Duncan, Duncan, & Stoolmiller, 1994; Raykov, 1994). Those approaches, however, either assume a cumulative latent evolutionary process or require that repeated measures be available to estimate the (potentially nonlinear) growth function.

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By contrast, and with respect to the first point, there is some evidence that developmental and change processes do not necessarily follow *monotonic* (i.e., always increasing or always decreasing) patterns of variation with time. In a reanalysis of Kohlberg's (1969) developmental data on moral judgments, for instance, Davison, Robbins, and Swanson (1978) showed that bell-shaped functions fitted the data better than monotonic ones. This means that while children are acquiring new abilities in moral reasoning, they make less and less use of previous modes of thinking, which variation may thus be described by a single-peaked function. In a clinical context, it is now well-known that behavior change is better described by bell-shaped patterns of evolution than by linear or logistic models (Prochaska, DiClemente, & Norcross, 1992; Prochaska, Velicer, DiClemente, Guadagnoli, & Rossi, 1991; Velicer, Rossi, Prochaska, & DiClemente, 1996).

With respect to the second point, repeated measurements are not easily obtained in clinical practice, so that a latent transition model for single-peaked patterns of change that would require a single measurement would be most useful in many applications. Recovering single-peaked patterns of change from single measurements is the focus of the present article. It is argued that unfolding models offer a quite flexible and powerful solution to these situations and open the way to new developments in the study of change.

The Unfolding Model of Data

Though linear models appear to be powerful in many situations, they are limited to the case when one may reasonably assume that there is a monotonic relationship between the latent phenomenon to be measured and the measure itself. Not all psychological phenomena will satisfy this condition, however. For instance, in the case when collected measures are related to the latent variable of interest by an inverse-U-shaped function, it is clear that no linear projection of the data will properly recover the latent variable. As can be seen using a simple (and somewhat artificial) example, this would be the case if, considering that performance on a task often varies as a single-peaked function of motivation around some ideal point (where motivation is sufficient but not excessive), we wanted to recover a measure of motivation from performance measurements. Clearly, there would be an indeterminacy in the estimation of motivation, because one level of performance may correspond to two distinct levels of motivation, below or above the ideal motivation point (Figure 1a). This would be a clear violation of the monotonicity condition for applying factor analysis.

There is one case, however, when factor analysis would nevertheless give an interesting approximation of the latent scores: when participants' ideal motivation points are distinct (Figure 1b). In this case only, the variance of participants' ideal points will be a source of information for estimating the latent motivations (Davison, 1977), and factor analysis will generally summarize this variance on the first factor, provided the participants' distribution on the latent dimension is approximately uniform. Generally, if latent scores on some latent construct are only known through a nonlinear response function, factor analysis will, of course, systematically give an overestimated number of components, because it mainly functions to recover linear orthogonal components. In the special case when the fundamental structure is unidimensional, as with developmental or temporal change data, and assuming a bell-shaped response function, factor analysis will give an artifactual two-component solution (Van Schuur & Kiers, 1994) instead of the theoretically expected unique dimension.

Unfolding analysis was primarily designed to deal with such single-peaked relationships between latent and manifest scores (Coombs, 1950). It may be thought of as a kind of multidimensional analysis, where the relationships between observed measures and latent scores to be recovered is of the inverse-U

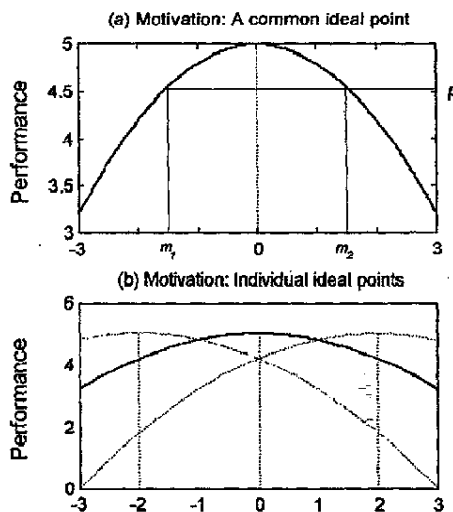


Figure 1. Single-peaked patterns of performance versus motivation. With a unique ideal motivation point (a), a given performance p may correspond to two latent values of motivation (m_1 and m_2), thus violating the monotonicity condition for applying factor analysis. However, a crude approximation of the latent dimension may be obtained with factor analysis in the case of individual ideal points (b). See Davison (1977).

type. It thus may be viewed as a kind of nonlinear factor analysis, with a nonlinearity constrained to be of second-order (first increasing, up to a maximum for some latent ideal point, and then decreasing). It is thus likely to be successfully applied whenever an ideal reference point may be supposedly underlying participants' responses, so that they will endorse items (or prefer objects, choose stimuli, etc.) located close to their ideal reference point and express less and less preference for items that are farther away on the scale in either direction.

It is, of course, crucial to establish whether a given phenomenon may properly be modeled as a sum of linear components or if some kind of nonlinearity exists in the way subjects respond to items. If this cannot be established from empirical or theoretical arguments, a risk exists that the final solution we try to interpret contains spurious factors. Van Schuur and Kiers (1994) proposed a number of diagnostics for distinguishing the cumulative and unfolding mechanisms of response. Though useful, they do not always allow one to firmly conclude that an unfolding model

is underlying, and the better way to proceed is probably to start from theoretical arguments in addressing this question as will be illustrated in this article.

Though initially designed for attitudinal data, the unfolding model has been successfully applied to developmental data as first suggested by Coombs and Smith (1973) and then illustrated, for instance, in the study of moral development (Davison et al., 1978) and learning goals development among students (Volel & Chalmers, 1992). As is clear from the unimodal assumption of the model, it will be actually relevant to developmental data analysis whenever processes characterizing each stage are supposed to successively replace processes characterizing previous stages. Participants will tend to indicate a greater use of processes characterizing a stage they are in, and a lower use of processes characterizing both lower and upper stages, thus displaying a unimodal distribution of their ratings on each process.

Obviously, such a developmental model relies on a different conceptualization of psychological change than do the better known cumulative models, such as Mokken, Rasch, or Guttman scaling. Whereas in cumulative models each stage is assumed to prepare the following in an integrative manner, so that earlier stages remain embedded in the later ones, in unfolding developmental models each stage is preparing the following while inhibiting the previous ones. Otherwise stated, the unfolding model of change assumes

that some processes are relevant in a given stage but no longer relevant as one moves along the developmental continuum.

In the measurement of change, we may thus reformulate the unfolding model of data as resulting both from a cumulative mechanism and from the negative feedback of each new process of change on the previous one in the change sequence. As a very simple example, negative emotionality toward one's behavior (e.g., smoking) may result in a search for social support, which in turn will diminish the negative emotional response. Social support may in turn increase involvement in personal action (Counterconditioning, for instance), which will finally diminish the need for social support (Figure 2). The resulting patterns of intensity variation with time for each of these processes will then be bell-shaped, first increasing up to a maximum and then decreasing.

In this formulation, unfolding models could be viewed as simple forms of (bipolar) nonlinear dynamical systems.

Despite these differences, recent developments in unfolding theory have ingeniously derived a probabilistic unfolding model from a double cumulative process, operating in reversed order on the underlying dimension (Andrich, 1995; Andrich & Luo, 1993), thus reconciling two different approaches to psychological measurement (see Andrich, 1996, for a historical discussion). Because derivation of this model

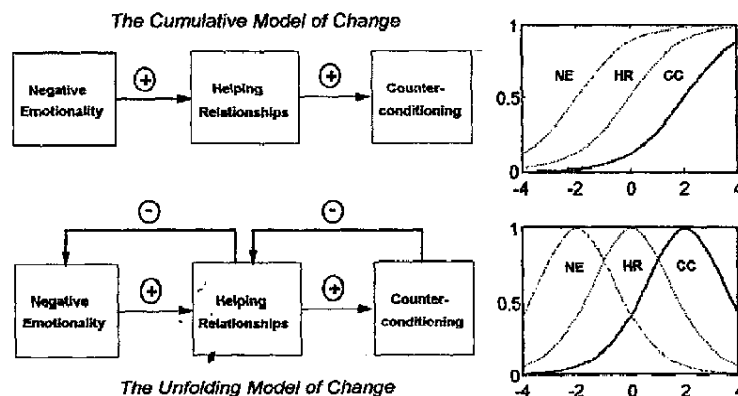


Figure 2. Plus signs indicate a positive feedback, minus signs a negative one. The unfolding model of change should be thought of as resulting from a joint acquisition-inhibition mechanism. For instance, negative emotionality (NE) leads to seeking (+) Helping Relationships (HR), which in turn may diminish (−) the negative feelings. Curves on the right-hand side are the resulting probabilities of agreeing with a corresponding item. CC = counterconditioning.

follows a clear rationale, which legitimates its application to the study of change (as is discussed below). I briefly present below Andrich's Hyperbolic Cosine Model (HCM) and its extension to the polytomous case proposed by Roberts and Laughlin (1996) under the name of Graded Unfolding Model (GUM; for details, see Andrich, 1995; Andrich & Luo, 1993; Roberts & Laughlin, 1996).

The probabilistic approach to psychological measurement has many nice properties, the first of them being that a shift from a qualitative (nominal or ordinal) level to a quantitative level of measurement is thus made possible. In this approach, the analysis does not bear on the rating itself but on its probability. This is statistically more satisfactory because ratings are essentially ordinal measures, whereas probabilities are on a ratio level of measurement. So, although metric unfolding algorithms also exist (Greenacre & Brown, 1986; Schönemann, 1970), or nonmetric algorithms in the multidimensional scaling (MDS) tradition (Takane, Young, & de Leeuw, 1977), the model used here belongs to the item response theory (IRT) class of models.

For a first example in the field of attitude measurement, let us consider an item of the form "I don't believe in capital punishment but I am not sure it isn't necessary." Although this would be considered rather a bad item in a classical (factor analytic) approach to measurement, it is a good one under the unfolding framework (Andrich, 1989; Andrich & Luo, 1993; Roberts & Laughlin, 1996; Wohlwill, 1963). Negative responses to such an ambivalent item are likely to be determined by two different motives: Subjects may refuse it either because they strongly believe in capital punishment or because they are strongly against capital punishment. Binary (disagree-agree) responses to such complex items are thus masking a true latent trichotomous response process with the following categories: disagreeing because one believes in capital punishment, agreeing and disagreeing because one does not accept capital punishment. Assuming a polytomous Rasch model for this latent trichotomous response process (Rasch, 1960), the probability of agreeing with this item is just the probability of the middle category response in a trichotomous Rasch model, whereas the probability of disagreeing with it is the summation of the two extreme response categories in the same model.

In more formal terms, and following Andrich's (1982) parameterization, for a subject i located in β facing an item j located in δ_j on the latent continuum,

the probability functions for each of the three response categories within a trichotomous Rasch model are of the form

$$P(X_{ij} = 0|\beta_i) = \frac{1}{\gamma_{ij}}, \quad (1)$$

$$P(X_{ij} = 1|\beta_i) = \frac{1}{\gamma_{ij}} \exp(\theta_j + \beta_i - \delta_j), \quad (2)$$

and

$$P(X_{ij} = 2|\beta_i) = \frac{1}{\gamma_{ij}} \exp[2(\beta_i - \delta_j)], \quad (3)$$

where X_{ij} is the response from subject i to item j , γ_{ij} is a normalizing factor to make the sum of all three probabilities equal to one, and θ_j is the half distance between the two intercategory thresholds.

The probability curves for these three determinants of response are shown in Figure 3. It can be seen that, as one considers increasing subjects' positions on the attitudinal continuum, from left to right, the probability of refusing the item for the first reason (for instance, being very much in favor of capital punishment) is first high (Interval 1) and then decreases, whereas the probability of agreeing with the item increases in the middle range (Interval 2), to finally decrease after a maximum has been reached, because the second source of refusal (for instance, being against capital punishment) is becoming predominant (Interval 3). The three attitudinal intervals (labeled 1,

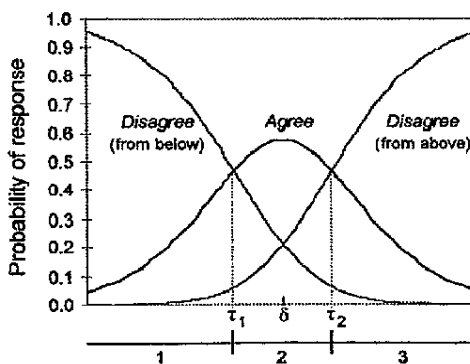


Figure 3. Probabilities of refusing or agreeing with an item, following Andrich and Luo's (1993) unfolding model. Moving along the latent continuum from left to right, we see that the item is first refused for a first reason, then is agreed to up to a maximum value, after which a second reason for refusing the item becomes predominant. τ = the threshold separating attitudinal intervals; δ = item location.

2, and 3 in the figure) are separated by two thresholds, τ_1 and τ_2 . The item's location (δ_j) corresponds to the higher probability of agreement, which is simply the midpoint of the two thresholds (this is the meaning of the θ_j parameter in the formulas above).

Because disagreement with the ambivalent item results from two latent sources that are not distinguished in the manifest response X' , the probability of a manifest disagree response may be written as a summation of Equations 1 and 3 (Andrich & Luo, 1993):

$$\begin{aligned} P(X'_{ij} = 0) &= P(X_{ij} = 0) + P(X_{ij} = 2) \\ &= \frac{1}{\gamma_{ij}} + \frac{\exp[2(\beta_i - \delta_j)]}{\gamma_{ij}} \\ &= \frac{1 + \exp[2(\beta_i - \delta_j)]}{1 + \exp(\theta_j + \beta_i - \delta_j) + \exp[2(\beta_i - \delta_j)]}, \quad (4) \end{aligned}$$

and the probability of agreeing is thus

$$\begin{aligned} P(X'_{ij} = 1) &= 1 - P(X'_{ij} = 0) = P(X_{ij} = 1) \\ &= \frac{\exp(\theta_j + \beta_i - \delta_j)}{1 + \exp(\theta_j + \beta_i - \delta_j) + \exp[2(\beta_i - \delta_j)]}, \end{aligned}$$

which may also be rewritten as

$$P(X'_{ij} = 0) = \frac{2 \cosh(\beta_i - \delta_j)}{\exp(\theta_j) + 2 \cosh(\beta_i - \delta_j)} \quad (5)$$

and

$$P(X'_{ij} = 1) = \frac{\exp(\theta_j)}{\exp(\theta_j) + 2 \cosh(\beta_i - \delta_j)} \quad (6)$$

where $\cosh(\cdot)$ is the hyperbolic cosine function—hence the name of the model.

In the IRT perspective, once a theoretical probability model has been designed, the β_i (i.e., subjects' locations) and δ_j (items' locations) parameters are estimated following the maximum-likelihood approach. The algorithm seeks β_i and δ_j values that maximize the probability of observing the raw data, given the assumed probability function. An interesting property of such models is that subjects and items play a symmetric role: They are both projected onto a common (often unidimensional) subspace. It thus becomes meaningful to compute a "distance" between a subject and an item, which is not possible under classical factorial models. Note that it is a general property of unfolding models to allow this simultaneous projection of subjects and items onto a common subspace. Also, in the MDS tradition, it is more usual to present unfolding analysis as a joint scaling of subjects and variables.

Andrich and Luo's (1993) reasoning can be readily extended to the polytomous case. Andrich (1996) and

Roberts and Laughlin (1996) have independently proposed a formulation for the multicategory case. In what follows, we rely on Roberts and Laughlin's GUM. In a very similar manner, these authors proposed that each manifest response, chosen out of a set of k possible responses, be assumed to result from the pooling of two underlying sources of agreement-disagreement. For instance, in the case of four manifest response categories (*strongly disagree*, *disagree*, *agree*, *strongly agree*), the probability of the *agree* response will be modeled as the sum of two latent sources of agreement, which are called "agree from below" and "agree from above," respectively (i.e., agreeing for the first or the second reason, which are mutually exclusive). Each test proposing a k -category response format will thus be analyzed with the assumption that $2k$ latent categories are in fact underlying the response mechanism—that is,

$$\begin{aligned} P(X'_{ij} = x|\beta_i) &= P(X_{ij} = x|\beta_i) \\ &+ P(X_{ij} = 2k - 1 - x|\beta_i) \quad (7) \end{aligned}$$

where X'_{ij} is the manifest response of subject i to item j , taking a value x out of k objective choices (from 0 to $k - 1$); X_{ij} is the latent response variable, taking one value out of $2k$ subjective categories (from 0 to $2k - 1$); and β_i is subject i 's location on the continuum.

Considering that the $2k$ latent response functions basically follow a rating scale model (Andrich, 1978b) of the form

$$P(X_{ij} = x|\beta_i) = \frac{\exp\left[x(\beta_i - \delta_j) - \sum_{l=0}^x \tau_l\right]}{\sum_{m=0}^{2k-1} \exp\left[m(\beta_i - \delta_j) - \sum_{l=0}^m \tau_l\right]}, \quad (8)$$

with τ_l denoting the thresholds separating two adjacent response categories on the latent dimension, the formal definition of the GUM is

$$\begin{aligned} P(X'_{ij} = x|\beta_i) &= \frac{\exp\left[x(\beta_i - \delta_j) - \sum_{l=0}^x \tau_l\right] + \exp\left[(2k - 1 - x)(\beta_i - \delta_j) - \sum_{l=0}^{2k-1-x} \tau_l\right]}{\sum_{m=0}^{k-1} \left\{ \exp\left[m(\beta_i - \delta_j) - \sum_{l=0}^m \tau_l\right] + \exp\left[(2k - 1 - m)(\beta_i - \delta_j) - \sum_{l=0}^{2k-1-m} \tau_l\right] \right\}} \quad (9) \end{aligned}$$

Though the form of the GUM is not as straightforward as, say, a simple one-parameter logistic model, its structure is clear: The two terms in the numerator correspond to the two latent determinants of response, whereas the summation in the denominator is just a normalizing factor.

In some way, the HCM and the GUM could be viewed as mixture models, because both are designed to model an observed probability function as the sum of two latent components. For this reason, Andrich's (1995) HCM and its extensions are natural candidates for the modeling of change processes, where items will be differently perceived when participants are below versus above the specific maturity level measured by each item.

Note that other cumulative models could be used as well in the same line. For instance, Roberts and Laughlin (1996) further proposed a partial credit GUM based on Masters' (1982) partial credit model, rather than the rating scale model.

However, one could be tempted to think that because this complex structure of data results from the implicit pooling of two basic reasons to reject the item, making these two reasons explicit in the response format should unfold the data prior to any analysis and thus allow for classical Rasch measurement. Although this is true for the previous example, this would not be possible in all situations as is now discussed.

What Is Change?

Numerous studies (DiClemente & Prochaska, 1982, 1985; DiClemente, Prochaska, Fairhurst, Velicer, Velasquez, & Rossi, 1991; Prochaska, Velicer, DiClemente, & Fava, 1988) have now given support to the idea that psychological change, in many areas, may be described in terms of processes and stages. There is an interaction between processes and stages of change in that participants in a given stage of change tend to predominantly use (or avoid) some of the processes.

Prochaska and DiClemente (1983) proposed four stages of change: These stages are, respectively, (a) *precontemplation* (or the *immotive* stage), (b) *contemplation* (expecting change but taking no action), (c) *action* (actual change), and (d) *maintenance* (defined as the period following a 6-month abstinence). An intermediate stage between contemplation and action, called *preparation*, has been added in later works (Prochaska & DiClemente, 1992). As the longitudinal

results to be discussed in this article have been reported in Prochaska et al. (1991) with the four-stage model, it is this simpler version that is used in what follows. In interaction with these four stages, 10 processes of change appear to cover much of the change dynamics (Prochaska, DiClemente, Velicer, Gimpil, & Norcross, 1985). Each of them appears to reach a peak in use at different stages. As to smoking cessation, Prochaska et al. (1991) gave a very careful report of longitudinal variations in the use of each process across stages. The first process to reach a peak is Social Liberation (or consciousness of alternative social roles and also of social pressure to refrain from smoking), which mainly characterizes the precontemplation stage. In the contemplation stage, smokers seem to have a marked negative emotional response (Dramatic Relief) toward smoking, they look for some support (Helping Relationships), and they begin to pay attention to available information concerning methods of quitting (Consciousness Raising or Information Processing). At the end of this stage, they become more aware of the effects of their smoking on the environment (Environmental Reevaluation).

As the action stage begins, Reinforcement Management is the first process to reach a maximum of use. At this stage, smokers tend to view quitting as a positive personal goal (Self-Reevaluation) in contrast to the more negative feelings that characterized the contemplation stage. As a preliminary form of action, they try to remove from their environment all things that could trigger a smoking desire (Stimulus Control).

Finally, engaging in the maintenance stage, ex-smokers will try to substitute alternative behaviors to smoking (Counterconditioning) and will rely more heavily on their personal will to control their behavior (Self-Liberation).

The practical relevance of this complex model has already been documented in many other applied areas—in psychotherapy (McConaughy, DiClemente, Prochaska, & Velicer, 1989; McConaughy, Prochaska, & Velicer, 1983), in the study of alcoholism (DiClemente & Hugues, 1990), in weight control (O'Connell & Velicer, 1988), in HIV prevention (Bowen & Trotter, 1995), and in exercise adoption (Marcus, Rossi, Selby, Niaura, & Abrams, 1992), among other behaviors—providing strong support for the hypothesis of common change principles across problem behaviors.

As the evolutionary patterns for the 10 processes are curvilinear (Prochaska et al., 1991; Velicer et al.,

1996), it is not surprising that confirmatory factor analyses tend to retain a second-order two-factor solution in the modeling of the correlation structure (Prochaska et al., 1988). In the context of factor analysis, at least two linear components are needed to model such a single-peaked relationship (just like two regressors, of first and second order, respectively, are needed when using linear regression to fit a quadratic relationship). These two higher order factors have been identified as, respectively, the experiential and behavioral components of the change process.

In the perspective of this article, however, the stage concept may be considered as an approximation of a smoker's position along a latent dynamic dimension. A numerical estimation of this position, provided it has some relationship to actual cessation, would represent a *change maturity index* that would make it possible to refine diagnoses and construct more specific intervention strategies.

This estimation is possible if we choose to take as a hypothesis the single-peaked pattern of variation of the change processes and thus submit measures of change to unfolding analysis. In the line of reasoning developed in the previous section, an item of the form "My dependency on cigarettes makes me feel disappointed in myself" is likely to be rejected for one of two distinct reasons: because the smoker does not consider smoking as so serious a problem or, to the contrary, because he or she has gained control over the addiction and has fewer reasons to feel disappointed. Responses to change maturity items are thus determined by two latent sources of refusal: low and high maturity of change, relative to the level of maturity specifically tapped by this item. These are the two disagree-from-below and disagree-from-above kinds of responses described by Andrich and Luo (1993).

It is noteworthy that in this very case where the latent dimension is of a temporal nature, *below* and *above* mean *before* and *after*, respectively, so that making underlying sources of disagreement explicit in the response format would not yield unfolded data: It is unlikely that smokers will be aware that they disagree with the item because they have not reached the stage of change that would make this attitude cognitively available, for instance. They cannot psychologically anticipate a stage they have not reached yet. Thus, by contrast with attitudinal scales, there is a fundamental asymmetry in the psychological perception of the change dimension, due to its temporal nature (as an exception, relapsers may, of course, re-

member what they used to think and do during previous quitting attempts).

Applying the GUM to change data is thus theoretically justified. The next section illustrates how this approach may be fruitful in applied research.

Application to Smoking Cessation

Method

Measures. A French version of the Processes of Change Questionnaire (DiClemente & Prochaska, 1985; Prochaska et al., 1988) was submitted to 140 smokers as part of an initial assessment session of a three-session hypnotic treatment for smoking. The Processes of Change Questionnaire is a 40-item questionnaire designed to measure the 10 basic change processes (four items per process). Translation, back-translation, and statistical equivalence of the French version with the original version at the score level have been described elsewhere (Noël, 1996; Noël & Bennani-Dosse, 1996). Statistical equivalence was shown to be almost perfect. The present study gives further validating results at the item level.

Participants. Participants were recruited through a newspaper advertisement. Treatment was free of charge. Participants' mean age was 34, men being significantly older than women (36 vs. 32, $p = .002$). The sample was rather well-educated, for 63% of the participants had a university degree. The overall mean dependence score on the 12-item Fagerström (1978) Tolerance Questionnaire was 6.36. Participants smoked a mean of 25 cigarettes a day. Participants were distributed in stages of change as follows: 3, 86, and 51 participants belonged to the precontemplation, contemplation, and preparation stages, respectively (of course, recruitment of smokers in precontemplation, action, or maintenance stages is highly unlikely in the clinical context).

Data Analysis

The publicly available GUMJML software (Roberts, 1998) was used for the analyses. This software implements Roberts and Laughlin's (1996) GUM, by the method of joint maximum likelihood (JML) estimation. As far as I know, no other software exists that would estimate a polytomous unfolding model in an IRT perspective, so comparison of results could not be made with other tools. However, this software has been very carefully designed, and in particular, it contains many safeguards against degeneration problems that would result from nonmonotonic likelihood func-

tions. In particular, bounds have been imposed on the maximum change in parameter values from one iteration to the next in the Newton-Raphson algorithm. Grid searches and a bisection algorithm are also implemented to control for extreme parameter values. Roberts's simulations have shown that accurate estimates could be obtained with as few as 100 respondents and 15 to 20 items.

Because in the GUM item discrimination parameters and intercategory thresholds are constrained to be equal for all items, a preliminary standardization of the data seemed desirable. The standardized scores were then arbitrarily recoded in five categories, according to the following evenly spaced cutoff points -1.2, -0.2, 0.80, 1.80, simply chosen to give enough weight to the extreme categories.

Two external sources are considered to test the validity of the solution: (a) We expect the resulting item ordering to reflect reasonably well the longitudinal data reported by Prochaska et al. (1991), and (b) we expect subjects' locations on the unfolding dimension to be significantly related to actual quitting. Treatment outcome was coded as 1 for participants' having not smoked at all for at least 7 days after the end of the program and 0 for participants who either had dropped out or failed to quit. Though dichotomous, such continuous abstinence measures are likely to be more robust than the number of cigarettes smoked, which is highly dependent on the way smokers compensate a decrease in absolute consumption by an increase in inhalation levels (Velicer, Prochaska, Rossi, & Snow, 1992).

Results

Item parameter estimates, asymptotic standard errors, and fit statistics are given in Table 1.

Both the chi-square and the infit index measure the discrepancy between observed data and the theoretically expected response function. The infit index is a squared standardized residual weighted by the theoretically expected information at each item location (Linacre & Wright, 1994). It is thus sensitive to discrepancies observed in high-information regions of the scale, which seems reasonable. In the standardized form reported in Table 1, it is assumed to have a mean near zero and a variance near unity and may thus be interpreted like a Student's *t*. As an additional diagnostic, Andrich's (1978a) chi-square was computed in the following way: Participants were first sorted by increasing location along the continuum, and clustered in seven consecutive class intervals of 20 par-

ticipants each. For each class, a mean location, a mean observed rating, the expected rating, and theoretical standard errors under the model were computed. The discrepancy between expected and observed ratings, given the theoretical variance, was used to compute a chi-square with 6 degrees of freedom over the seven subgroups, for each item. The resulting observed ratings (plotted as dots) and expected ratings (plotted as solid lines) are displayed in Figure 4. Black squares indicate items that showed poor fit, following either one of the fit statistics.

Note that, though the infit index is robust in the context of Rasch measurement, these results should, of course, be taken with some caution because fit indices' properties are not yet well explored under the HCM and GUM.

Table 2 shows item parameters and wordings.

Out of 40 items, both the standardized infit index and Andrich's chi-square indicate 13 ill-fitting items (with probabilities smaller than or equal to .05): 2 items from the Dramatic Relief subscale ("I react emotionally to warnings about smoking cigarettes," "Remembering studies about illnesses caused by smoking upsets me"), 3 from the Social Liberation subscale ("I find society changing in ways that make it easier for the non-smoker," "I notice that public places have sections set aside for smokers," "I see 'No Smoking' signs in public buildings"), 2 items from the Self-Reevaluation subscale ("My dependency on cigarettes makes me feel disappointed in myself," "I reassess the fact that being content with myself includes changing the smoking habit"), 1 from the Helping Relationships subscale ("Special people in my life accept me the same, whether I smoke or not"), 1 from the Stimulus Control subscale ("I keep things around my place of work that remind me not to smoke"), 1 from the Self-Liberation subscale ("I tell myself I can choose to smoke or not"), and 3 from the Counterconditioning subscale ("When I am tempted to smoke, I think about something else," "Instead of smoking I engage in some physical activity," "I do something else instead of smoking when I need to relax or deal with tension").

That only 13 out of 40 items show poor fit to the model was judged quite an encouraging result. Out of the 10 processes, Social Liberation and Counterconditioning appear to be the most badly represented. As to Social Liberation, some cultural particularity may have played a role, because until recently, social pressure against smoking has not been as important in France as in the United States. Also note that, because

Table 1
Item Parameter Estimates and Fit Statistics

Process	Location	ASE	Standardized infit	Item χ^2	<i>p</i>	Andrich's χ^2	<i>p</i>
Dramatic Relief	-.538	.097	-1.79	114.21	.939	9.075	.1694
	-.494	.096	1.04	155.66	.158	15.895	.0143
	-.458	.096	0.79	151.64	.219	14.208	.0274
	-.396	.095	-1.13	123.22	.828	8.349	.2136
Social Liberation	-.384	.095	2.82	186.27	.005	17.231	.0085
	-.318	.095	1.75	167.44	.050	12.417	.0533
	-.253	.094	3.39	196.85	.001	13.487	.0359
	-.190	.093	-0.36	134.12	.601	3.020	.8064
Information Processing	-.510	.096	0.05	140.19	.456	5.663	.4620
	-.357	.095	-3.99	87.71	1.000	3.625	.7272
	-.101	.093	0.45	146.32	.319	8.818	.1841
	-.099	.093	-3.39	94.41	.999	4.984	.5459
Environmental Reevaluation	-.167	.093	-1.51	117.93	.902	8.256	.2200
	-.112	.093	-2.38	106.61	.981	1.838	.9340
	-.051	.092	-0.62	130.34	.688	8.293	.2174
	-.049	.092	-2.05	110.86	.962	3.136	.7917
Self-Reevaluation	-.150	.093	-0.81	127.63	.746	10.182	.1172
	-.074	.092	2.56	181.65	.009	33.662	.0000
	.007	.092	-2.86	100.64	.994	2.943	.8160
	.054	.092	1.74	167.42	.051	12.981	.0433
Reinforcement Management	-.038	.092	-1.04	124.43	.807	10.978	.0891
	.087	.092	-0.98	125.16	.794	4.962	.5487
	.151	.092	-0.87	126.69	.765	3.058	.8015
	.187	.092	-1.67	115.65	.926	3.343	.7648
Helping Relationships	.031	.092	-0.82	127.41	.750	7.752	.2569
	.132	.092	3.72	203.73	.000	61.513	.0000
	.150	.092	0.03	139.86	.464	12.285	.0559
	.226	.092	0.90	153.53	.189	8.905	.1790
Stimulus Control	.142	.092	0.33	144.54	.356	9.670	.1393
	.201	.092	-1.09	123.53	.822	5.626	.4664
	.255	.092	-2.55	104.08	.988	9.841	.1315
	.309	.092	-0.16	137.01	.532	17.558	.0074
Self-Liberation	.087	.092	1.29	159.94	.108	2.910	.8200
	.374	.093	2.86	187.97	.004	10.030	.1234
	.412	.093	-3.75	89.46	1.000	2.069	.9132
	.434	.094	0.46	146.64	.312	5.622	.4669
Counter conditioning	.144	.092	-1.30	120.75	.866	18.643	.0048
	.284	.092	0.36	145.07	.345	4.071	.6671
	.478	.094	-1.68	115.13	.931	14.851	.0214
	.593	.096	1.16	158.20	.127	23.274	.0007

Note. Boldface values indicate ill-fitting items ($p < .05$). For comparison with previous studies, items are clustered here according to the processes they are supposed to measure within DiClemente and Prochaska's (1985) stage-of-change model (as labeled in the first column). For each Andrich's χ^2 in the table, $df = 6$. ASE = asymptotic standard error.

the sample was recruited in a clinical context, participants were unlikely to express opinions and attitudes that are more characteristic of the earlier stages of change, and likewise, they were unlikely to engage in sophisticated behaviors that are more characteristic of recent quitters. Consequently, one may expect the

most extreme items, at both ends of the continuum, to be badly scaled.

A global comparison of the whole scale against a perfect model, given the estimated parameters, gave a poor fit: likelihood ratio χ^2 (5417, $N = 140$) = 14014.089, $p < .0000$. This is not too surprising given

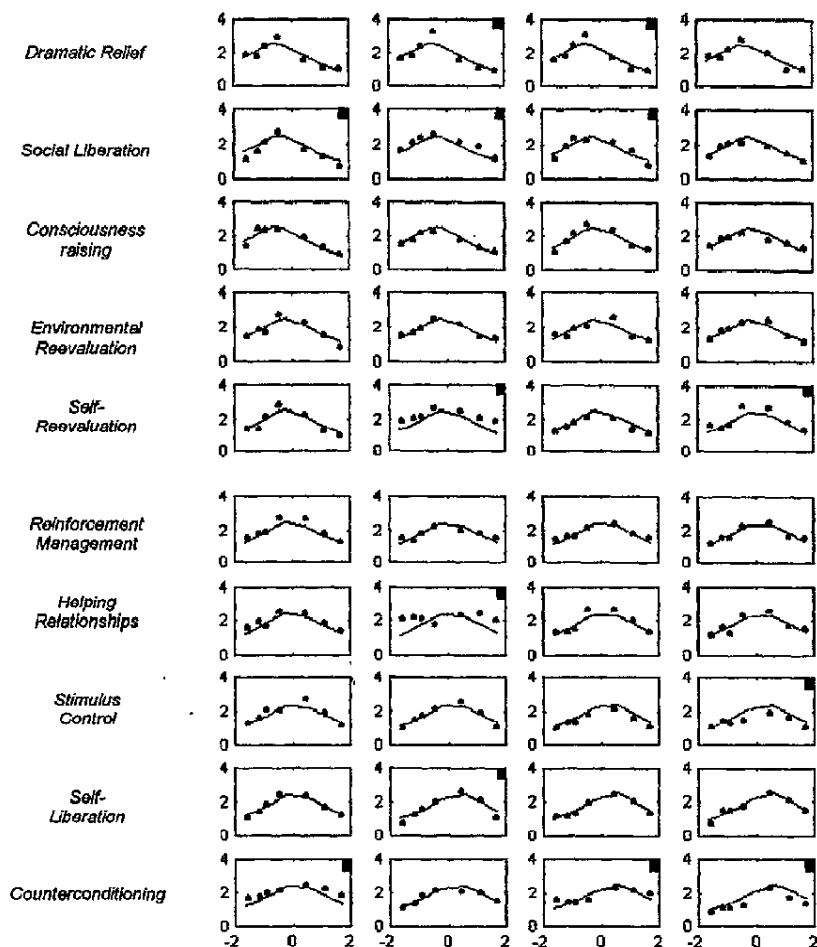


Figure 4. Participants, ordered by location, have been clustered in seven consecutive class intervals of 20 participants each. For each of the items, the solid line is the theoretically expected response function, and the dots are the observed average responses from each subgroup. Black squares indicate ill-fitting items ($p < .05$).

that the scale was not primarily designed under the unfolding framework, and given the strong parametric constraint of equal discrimination and threshold parameters implied by the model. Threshold estimates, constrained to be the same across items, were -3.01 , -0.80 , -0.45 , 1.24 .

The 10 best items (1 from each subscale) are shown in Figure 5, along with a plot of the observed and

expected ratings, item parameters and wordings, and significance thresholds.

The bell-shaped pattern of response is clear for all items, around their specific locations on the cognitive-behavioral continuum. This means that participants expressed less and less affinity with an item when far from it in either direction (i.e., when below or above the specific level of maturity basically mea-

Table 2
Items' Locations and Wordings

Theoretical process	Item unfolding location	Item wording
Dramatic Relief	-0.54	Dramatic portrayals of the evils of smoking affect me emotionally
	-0.49	I react emotionally to warnings about smoking cigarettes
	-0.46	Remembering studies about illnesses caused by smoking upsets me
Social Liberation	-0.40	Warnings about health hazards of smoking move me emotionally
	-0.38	I find society changing in ways that make it easier for the non-smoker
	-0.32	I see "No Smoking" signs in public buildings
	-0.25	I notice that public places have sections set aside for smokers
Consciousness Raising	-0.19	I notice that non-smokers are asserting their rights
	-0.51	I recall articles dealing with the problems of quitting smoking
	-0.36	I think about information from articles and advertisements on how to stop smoking
	-0.10	I recall information people have personally given me on the benefits of quitting smoking
Environmental Reevaluation	-0.10	I recall information people have personally given me on how to stop smoking
	-0.17	I consider the view that smoking can be harmful to the environment
	-0.11	I am considering the idea that the world around me would be a better place without my smoking
	-0.05	I stop to think that smoking is polluting the environment
Self-Reevaluation	-0.05	I am considering the belief that people quitting smoking will help to improve the world
	-0.15	I consciously struggle with the issue that smoking contradicts my view of myself as a caring and responsible person
	-0.07	My dependency on cigarettes makes me feel disappointed in myself
	0.01	I get upset when I think about my smoking
Reinforcement Management	0.05	I reassess the fact that being content with myself includes changing the smoking habit
	-0.04	Other people in my daily life try to make me feel good when I don't smoke
	0.09	I reward myself when I don't smoke
	0.15	I can expect to be rewarded by others if I don't smoke
Helping Relationships	0.19	I am rewarded by others if I don't smoke
	0.03	I have someone whom I can count on when I'm having problems with smoking
	0.13	Special people in my life accept me the same, whether I smoke or not
	0.15	I can be open with at least one special person about my experience with smoking
Stimulus Control	0.23	I have someone who listens when I need to talk about my smoking
	0.14	I remove things from my home that remind me of smoking
	0.20	I remove things from my place of work that remind me of smoking
	0.26	I put things around my home that remind me not to smoke
Self-Liberation	0.31	I keep things around my place of work that remind me not to smoke
	0.09	I make commitments not to smoke
	0.37	I tell myself I can choose to smoke or not
	0.41	I tell myself I am able to quit smoking if I want to
Counterconditioning	0.43	I tell myself that if I try hard enough I can keep from smoking
	0.14	When I am tempted to smoke, I think about something else
	0.28	I find that doing other things with my hands is a good substitute for smoking
	0.48	Instead of smoking I engage in some physical activity
	0.59	I do something else instead of smoking when I need to relax or deal with tension

Note. Items are clustered according to the process they are supposed to measure within DiClemente and Prochaska's (1985) stage-of-change model. Processes are ordered by increasing mean location (averaged over their four items) along the continuum.

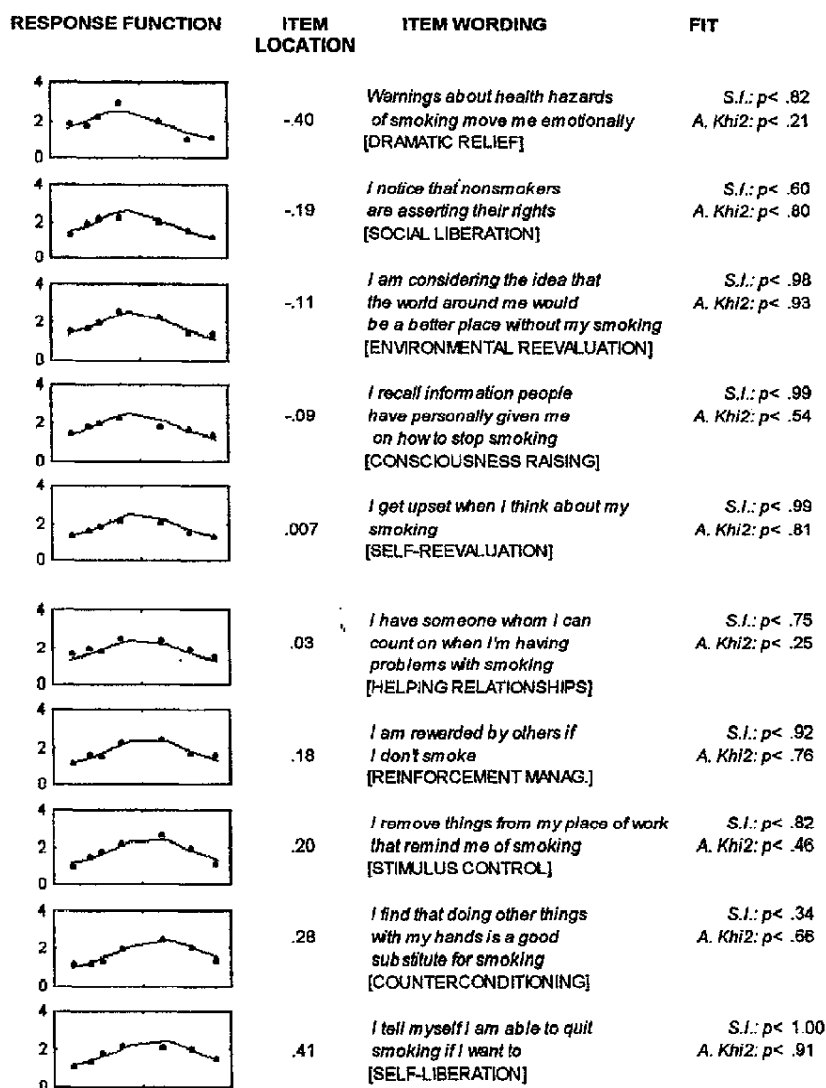


Figure 5. Observed and theoretically expected response functions for the 10 best items. The unimodal pattern of response is quite clear, around items' locations, indicating that participants far from the item, in both directions, express lower preference for it. S.I. = standardized infit, A. Khi2 = Andrich's chi-square; Manag. = Management.

sured by each item). On the extreme right, the response pattern evolves more and more toward a cumulative monotonic function, for those processes not yet reached by a majority of participants. A unimodal response function thus appears to model the data correctly. In the perspective of the present article, global fit to the data is also to be estimated from theoretical considerations and external validations.

Convergence With Longitudinal Data

A first validation can be done by checking the process ordering recovered by unfolding analysis with the ordering emergent from longitudinal studies (Prochaska et al., 1992; Prochaska et al., 1991). As my analysis scaled items, and because many previous results have been reported as processes scores (i.e., a sum of four items), I computed mean process locations (averaged over the locations of their four characteristic items). This is just for comparison with the stage-of-change model, because in the perspective of this study, the factor model is inadequate and simply captures segments of a latent continuum. Figure 6 shows items as dots, horizontally ordered by their estimated unfolding locations and vertically clustered by process.

Dramatic Relief (negative emotionality associated with smoking) is the first process on the left end of the latent dimension, closely followed by Social Liberation items. These two processes were also representative of very early stages of change in a previous study (Prochaska et al., 1991). It should be noted, however, that in this last study, Social Liberation had

appeared predominant in the precontemplation stage. Consciousness Raising (or Information Processing) then follows, but its four characteristic items do not appear well-clustered on the continuum. Two of them are located near Dramatic Relief items, whereas the two others appear farther on the right. Interestingly, the latter are two items implying other persons as a source of information ("I recall information people have personally given me on the benefits of quitting smoking," and "I recall information people have personally given me on how to stop smoking"). Thus, they might be considered as complex items, tapping both Information Processing and some helping external support.

A step ahead on the continuum, Environmental Reevaluation appears as a well-clustered process, which had been previously described as characteristic of the end of the contemplation stage. Self-Reevaluation and Reinforcement Management then appear, well clustered and close together, once again in good convergence with longitudinal results. The unfolding algorithm also located the Helping Relationships items in this region, whereas they had been previously reported as characteristic of earlier stages. A closer look at variations curves reported for Helping Relationships by Prochaska et al. (1991), however, suggests a bimodal curve, with one peak in the contemplative stage and another in the action stage. It may be hypothesized that Helping Relationships items may cover either external incitement to change (before change is engaged) or support (when active change has begun). Moreover, it does not seem too surprising

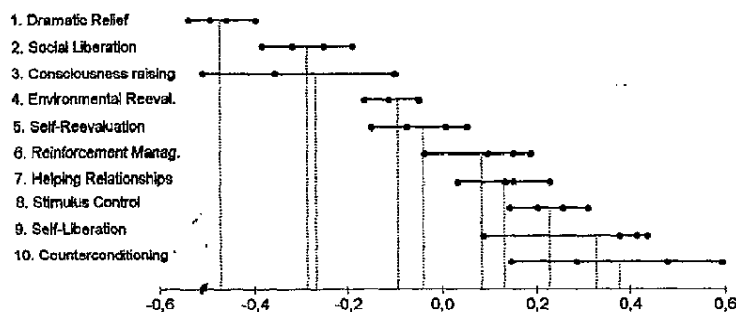


Figure 6. The 40 items (shown as dots) are horizontally ordered by locations and vertically ordered by process. For comparison with previous results based on process scores, process mean locations (averaged over the four characteristic items within each process) are indicated by the dashed lines. From left to right and top to bottom, items are of less cognitive and of more behavioral a nature. Reeval. = Reevaluation; Manag. = Management.

that Helping Relationships is located close to Reinforcement Management, of which three out of four items involve being rewarded by someone else. However, unfolding estimates were here in divergence with the longitudinal data. Stimulus Control is the following predominant change process of the action stage as expected. Finally, Self-Liberation and Counterconditioning, previously described as characteristic of the last steps in the change dynamics, are positioned on the extreme right end of the graph.

Globally, the change dynamics may be summarized as the following psychological sequence: (a) negative evaluation of present behavior, (b) information taking, (c) positive reevaluation of change, and (d) action. Other formulations are also possible: From left to right, participants are moving from negative (Dramatic Relief) to positive emotionality (Reinforcement Management, Helping Relationships), and from cognition (Information Processing) to action (Counterconditioning). Note that any arbitrary segmentation of the continuum would be equally relevant and that the present analysis has the advantage to recover a continuous dimension rather than a stage sequence. In view of these results, it is now possible to understand what factor analysis actually yielded in previous studies (Prochaska et al., 1988): The factors are clusters of items that are linked by a neighborhood relationship along a single continuum. This does not appear as a single factor because the contiguity relationship between them is not simply linear or monotonic but curvilinear. An arbitrary number of "factors" is thus needed to map the whole continuum from left to right

as a linear combination of latent (correlated) components.

For comparison purposes, Table 3 summarizes the convergence between the present unfolding model of change with the stage-of-change model.

Here again, processes' "centroids" are used for this comparison. The major deviations from the expected ordering concern Social Liberation (which is badly represented, as indicated before) and Helping Relationships, which appear more characteristic of later stages of change in our analyses. Given that these results were obtained from a single measurement, however, the convergence with the longitudinal data is quite striking.

Relationship to Cessation

It is now natural to examine the link of participants' parameters with some external behavioral criterion, just like we checked the convergence of item parameters with longitudinal data. For each participant, actual cessation or failure to quit had been registered (with failure to quit including participants who had dropped out from the treatment protocol). A Student's *t* test performed on subjects' parameters and comparing successes ($n_s = 48$, $M_s = 0.20$, $SD_s = 1.138$) and failures ($n_f = 92$, $M_f = -0.26$, $SD_f = 1.130$) yielded a significant difference value ($t = 2.313$, $p < .02$). Participants who actually quit are thus located significantly closer to the right end of the cognitive-behavioral continuum.

Figure 7 displays a LOWESS (locally weighted smoothing scatterplot) smoothing (Cleveland, 1979)

Table 3
Correspondence of Processes' Mean Locations and the Stage-of-Change Model

Process	Mean locations	Stage of change
Dramatic Relief	-.47	Precontemplation
Social Liberation	-.29	
Consciousness Raising	-.27	
Environmental Reevaluation	-.09	
Self-Reevaluation	-.04	Action
Reinforcement Management	.10	
Helping Relationships	.13	
Stimulus Control	.23	
Self-Liberation	.33	
Counterconditioning	.37	Maintenance

Note. Because the analysis scaled items, processes' locations reported here were computed as a mean location, averaged over the four items measuring each process.

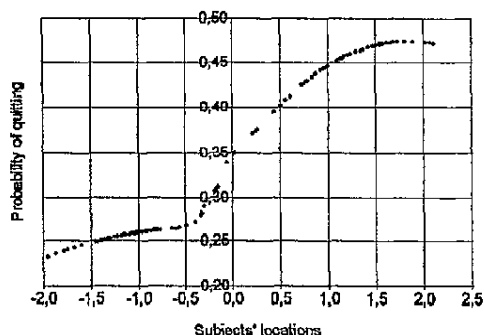


Figure 7. Participants' actual behavior (1 = quit, 0 = failed or dropped out) has been nonparametrically regressed on their estimated locations on the continuum. Clearly, participants closer to the behavioral end of the continuum have a higher probability of quitting.

of the binary outcome variable on subjects' parameters, which gives an estimation of the locally increasing densities of successes along the continuum. This algorithm is a nonparametric regression procedure, which proceeds by a locally weighted polynomial regression, specially designed not to be too sensitive to rare outliers, while capturing the main trend of a relationship. A clear increasing monotonic pattern of the success probability emerges as a function of participants' locations.

Both external validation criteria, at the item and subject level, respectively, thus strongly support the relevance of the unfolding model in the study of change in smoking cessation.

Discussion

Though unfolding models have been available for years now (Coombs, 1950; Coombs & Smith, 1973), they are not in wide use yet. One reason for that may be that the response mechanism the model implies is less simple than the cumulative one. Another reason may be that the first operationalizations of the model have shown some practical limitations. Coombs' combinatorial algorithms were limited as to the number of variables and participants they could handle. Though many powerful unfolding models in the MDS tradition were developed in the 1970s and 1980s that were not limited in this respect (Greenacre & Browne, 1986; Heiser, 1981; Schöemann, 1970; Takane et al., 1977), some researchers have warned against the degeneration problems frequently encountered with

those approaches (Van Schuur, 1993b; Van Schuur & Kiers, 1994).

In an earlier work (Noël & Bennani-Dosse, 1996), using Greenacre and Browne's (1986) unfolding algorithm on processes-of-change scores (i.e., scores resulting from summing four items belonging to a common theoretical process), we found processes' locations to be strangely clustered at the extremities of the continuum, even though their ordering was theoretically meaningful (with cognitive processes at one end and behavioral processes at the other end), and though subjects' locations were also significantly related to actual quitting. To better appreciate why such "clustered" solutions are often found with unfolding algorithms in the MDS perspective, one may consider them as standard MDS analyses, trying to scale points in a low-dimensional space from their interdistances, but performed on a supermatrix including both variables and subjects, where only subjects-variables distances are known. Large parts of the interdistances matrix are thus missing, hence the instability of the solutions.

I believe that recent developments in probabilistic item response models should renew interest in the unfolding paradigm. Among them, parametric models impose enough constraints to avoid degenerate solutions, provided the model holds. The evenly spread scaling of items obtained in the present study, by contrast with the one obtained by an MDS approach, supports this view. Moreover, recent extensions of unfolding models to the polytomous case, and software development (GUMJML, Roberts, 1998; MUDFOLD, Van Schuur, 1993a, 1993b), make them more appropriate to many cases of applied research.

From a computational standpoint, it should be noted that the present results were obtained with a JML estimation procedure (i.e., participant and item parameters were estimated jointly in an alternating maximization process). This procedure is known to give biased estimates in the context of Rasch measurement—at least when the number of variables is small. Though Roberts and Laughlin's (1996) simulations using the JML approach gave reasonably accurate results, some preliminary results of the same authors using a marginal maximum likelihood (MML) algorithm (i.e., estimating parameters on one subset at a time) suggest that this last approach gives still better estimates. A similar argument also led Takane (1998) to adopt the MML approach in the estimation of his unfolding choice model for binary data. The development of tools for unfolding polytomous data using the MML approach is thus called for.

From a theoretical standpoint, unfolding models are likely to be well adapted to the measurement of complex psychological phenomena resulting from the interplay of two opposite mechanisms (Van Schuur & Kiers, 1994). In effect, response functions obtained in such cases are likely to be unimodal, each mechanism having an inhibitive effect on the other.

As an additional example, a still unresolved issue in factorial studies on mood is the determination of whether positive and negative affectivity are independent or negatively correlated constructs, some authors bringing empirical support to the first model (Watson & Tellegen, 1985) whereas others have reported non-negligible negative correlations (Green, Goldman, & Salovey, 1993; Russell, 1979). One explanation for this divergence might be that a nonlinear and reciprocally inhibitive relationship exists between positive and negative mood, which, depending on sampling error, would appear as either null or negative correlations in empirical studies. Applying unfolding analysis to such data might be interesting. Many psychological phenomena are thus likely to be properly modeled as a dynamical interplay between two latent components, for which unfolding analysis would be relevant.

The unimodal pattern of variation is also probably partly responsible for the pessimistic conclusions that have long prevailed about the hope of establishing a clear relationship between expressed intentions and actual behavior. I believe that correlation coefficients are likely to be poor estimates of the actual relationship between attitude and behavior indicators, because of the unimodal pattern of variation of such indicators with time. Clearly, cognitive processes (intention to change) trigger action, but action in turn is likely to decrease conflict and negative emotional investment in change. The unfolding model of change thus gives a very elegant solution to this problem, commonly addressed in social and clinical psychology, as already suggested by Andrich and Styles (in press) in the study of attitudes toward environment. In this last study, attitude and behavioral statements were found to be located systematically on different regions of a single continuum. It is my view that intention and behavior should then be conceived as belonging to a common latent dimension, rather than two distinct constructs, the unimodal pattern of response resulting in artifactually weak correlations between them and erroneously giving a two-factor solution in factor analyses.

However, a possible limitation of the current para-

metric unfolding models might be that the symmetry inherent in most unfolding response functions (Andrich & Luo, 1993; Roberts & Laughlin, 1996; Verhelst & Verstralen, 1993) is somewhat constraining as to change data. Prochaska et al.'s (1991) results seem to indicate that in the unimodal pattern, at least for some processes, the decrease may be slower than the increase, just as if participants tended to maintain the processes' effects for some time. Possible refinements of the present analysis might thus be to construct an appropriate asymmetric parametric model or, alternatively, to turn to nonparametric approaches (Post & Snijders, 1993; Van Schuur, 1993a, 1993b), which only assume unimodality, with no hypothesis on the exact function shape, for estimating subjects and item parameters. This is an important technical question, for positively skewed item response functions, for instance, would be erroneously interpreted by common parametric models as characterizing more advanced stages of change than is the case in reality. Maybe this is what happened in the present study with the Helping Relationships process.

Another limitation of this research is that only a clinical sample was studied, which means that, following the stage-of-change terminology, most smokers involved were in the contemplative (second) or preparation (third) stages of change. As the model used here is parametric, this is not too serious a problem, because it imposes enough constraint on the solution to recover meaningful results as has been shown. However, an interesting extension of the present research would be to replicate the analysis with a broader sample, including, for instance, immotives, recent quitters, and relapsers. One may expect that the scaling of extreme items, at both ends of the scale, would be more precise.

Finally, parametric probabilistic models have another attractive feature: They allow for item banking. By sharing a common parametric model, independent researchers might contribute to the selection of best fitting items, for which parameters and external validations would be well-known. From a practical point of view, participants' readiness to change could be estimated with respect to fixed item parameters as established in calibration studies. This could be done by maximizing a likelihood on subjects parameters, item parameters being held fixed to their calibration values. It may be of some interest, for instance, to clinical psychologists if some kind of computerized adaptive testing (see Dodd, De Ayala, & Koch, 1995, for a review) were available for the clinical assess-

ment of readiness to change for any given problem behavior. Volet and Chalmers (1992) showed how measurement of change in learning goals among students was made possible by examining students' locations on an unfolding continuum at two different time points. A very similar approach might be used in the assessment of clinical change. I believe designing clinical instruments on the basis of a scale construction process that would assume the unfolding mechanism at the core of psychological change would be a preliminary step in this direction.

References

- Andrich, D. (1978a). Application of a psychometric rating model to ordered categories which are scored with successive integers. *Applied Psychological Measurement*, 2, 581-594.
- Andrich, D. (1978b). A rating formulation for ordered responses categories. *Psychometrika*, 43, 561-573.
- Andrich, D. (1982). An extension of the Rasch model for ratings providing both location and dispersion parameters. *Psychometrika*, 47, 105-113.
- Andrich, D. (1989). A probabilistic IRT model for unfolding preference data. *Applied Psychological Measurement*, 13, 193-216.
- Andrich, D. (1995). Hyperbolic cosine latent trait models for unfolding direct responses and pairwise differences. *Applied Psychological Measurement*, 19, 269-290.
- Andrich, D. (1996). A hyperbolic cosine latent trait model for unfolding polytomous responses: Reconciling Thurstone and Likert methodologies. *British Journal of Mathematical and Statistical Psychology*, 49, 347-365.
- Andrich, D., & Luo, G. (1993). A hyperbolic cosine latent trait model for unfolding dichotomous single-stimulus responses. *Applied Psychological Measurement*, 17, 253-276.
- Andrich, D., & Styles, I. (in press). The structural relationship between attitude and behavior statements from the unfolding perspective. *Psychological Methods*.
- Bock, R. D. (1972). Estimating item parameters and latent ability when responses are scored in two or more nominal categories. *Psychometrika*, 37, 29-51.
- Bowen, A. M., & Trotter, R. (1995). HIV risk in IV drug users and crack smokers: Predicting stage of change for condom use. *Journal of Consulting and Clinical Psychology*, 63, 238-248.
- Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, 74, 829-836.
- Coombs, C. H. (1950). Psychological scaling without a unit of measurement. *Psychological Review*, 57, 145-158.
- Coombs, C. H., & Smith, J. E. K. (1973). On the detection of structures in attitudes and developmental processes. *Psychological Review*, 80, 337-351.
- Davison, M., Robbins, A., & Swanson, D. (1978). Stage structure in objective moral judgements. *Developmental Psychology*, 14, 137-146.
- Davison, M. L. (1977). On a metric unidimensional unfolding model for attitudinal and developmental data. *Psychometrika*, 42, 523-547.
- DiClemente, C. C., & Hugues, S. O. (1990). Stages of change profiles in alcoholism treatment. *Journal of Substance Abuse*, 2, 217-235.
- DiClemente, C. C., & Prochaska, J. O. (1982). Self-change and therapy change of smoking behavior: A comparison of processes of change in cessation and maintenance. *Addictive Behaviors*, 7, 133-142.
- DiClemente, C. C., & Prochaska, J. O. (1985). Processes and stages of change: Coping and competence in smoking behavior changed. In S. Schiffman & T. A. Wills (Eds.), *Coping and substance abuse* (pp. 319-343). New York: Academic Press.
- DiClemente, C. C., Prochaska, J. O., Fairhurst, S. K., Velicer, W. F., Velasquez, M. M., & Rossi, J. S. (1991). The process of smoking cessation: An analysis of precontemplation, contemplation, and preparation stages of change. *Journal of Consulting and Clinical Psychology*, 59, 295-304.
- Dodd, B. G., De Ayala, R. J., & Koch, W. R. (1995). Computerized adaptive testing with polytomous items. *Applied Psychological Measurement*, 19, 5-22.
- Duncan, T. E., Duncan, S. C., & Stoolmiller, M. (1994). Modeling developmental processes using latent growth structural equation methodology. *Applied Psychological Measurement*, 18, 343-354.
- Fagerström, K. O. (1978). Measuring degree of physical dependence to tobacco smoking with reference to individualization of treatment. *Addictive Behaviors*, 3, 235-241.
- Fischer, G. H. (1989). An IRT-based model for dichotomous longitudinal data. *Psychometrika*, 54, 599-624.
- Fischer, G. H., & Parzer, P. (1991). An extension of the rating scale model with an application to the measurement of change. *Psychometrika*, 56, 637-651.
- Green, D. P., Goldman, S. L., & Salovey, P. (1993). Measurement error masks bipolarity in affect rating. *Journal of Personality and Social Psychology*, 64, 1029-1041.
- Greenacre, M. J., & Browne, M. W. (1986). An efficient alternating least squares algorithm to perform multidimensional unfolding. *Psychometrika*, 51, 241-250.

- PM3001487377

- Thurstone, L. L. (1928). A law of comparative judgments. *Psychological Review*, 34, 278-286.
- Van Schuur, W. H. (1993a). MUDFOLD. *Quantitative Methods*, 42, 39-54.
- Van Schuur, W. H. (1993b). Nonparametric unidimensional unfolding for multicategory data. *Political Analysis*, 4, 41-73.
- Van Schuur, W. H., & Kiers, H. A. L. (1994). Why factor analysis often is the incorrect model for analyzing bipolar concepts, and what model to use instead. *Applied Psychological Measurement*, 18, 97-110.
- Velicer, W. F., Prochaska, J. O., Rossi, J. S., & Snow, M. G. (1992). Assessing outcome in smoking cessation studies. *Psychological Bulletin*, 111, 23-41.
- Velicer, W. F., Rossi, J. S., Prochaska, J. O., & DiClemente C. C. (1996). A criterion measurement model for health behavior change. *Addictive Behaviors*, 21, 555-584.
- Verhelst, H. D., & Verstralen, H. H. F. M. (1993). A stochastic unfolding model derived from the partial credit model. *Quantitative Methods*, 42, 73-92.
- Volet, S. E., & Chalmers, D. (1992). Investigation of qualitative differences in university students' learning goals, based on an unfolding model of stage development. *British Journal of Educational Psychology*, 62, 17-34.
- Watson, D., & Tellegen, A. (1985). Toward a consensual structure of mood. *Psychological Bulletin*, 98, 219-235.
- Wohlwill, J. F. (1963). The measurement of scalability for non-cumulative items. *Educational and Psychological Measurement*, 23, 543-555.

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- For the **Journal of Experimental Psychology: Human Perception and Performance**, submit manuscripts to David A. Rosenbaum, PhD, Department of Psychology, Pennsylvania State University, 642 Moore Building, University Park, PA 16802-3104.

Manuscript submission patterns make the precise date of completion of the 1999 volumes uncertain. Current editors, Charles R. Schuster, PhD; Clara E. Hill, PhD; and Thomas H. Carr, PhD, respectively, will receive and consider manuscripts through December 31, 1998. Should 1999 volumes be completed before that date, manuscripts will be redirected to the new editors for consideration in 2000 volumes.